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Understanding the Role of Income in Personal Happiness: A Comprehensive PSM Analysis in the United States

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This study examines the relationship between income and individual happiness in the United States using propensity score matching (PSM) analysis. Results reveal that income has a significant impact on individual happiness, with higher income levels associated with increased happiness. The research uses the General Social Survey (GSS) 2022, which marks the beginning of a shift to a mixed-mode survey, incorporating the delivery of both face-to-face and online questions. Employing the general principle of core hypotheses, the analysis aims to understand the causal relationship between income and happiness. The results suggest that improving income could be an effective strategy for increasing individuals' levels of happiness. The study underlines the importance of considering income as a factor that promotes individual well-being and happiness.

JEL Classification: D31, I31
Keywords: Individual Happiness, Income, Propensity Score Matching (PSM), United States, GSS 2022

1. INTRODUCTION

Happiness, a key aspect of individual well-being, has been widely studied in the US context, particularly in relation to income. Notable research has associated higher income with a reduction in daily sadness, as demonstrated by the results of Stevenson & Wolfers (2008). However, the impact on daily happiness appears to be negligible, suggesting that while increased income may alleviate some emotional distress, it may not contribute significantly to overall happiness.

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Authors' Note: For the purposes of this document, it is essential to state that I have no conflicts of interest to disclose. As a professional concerned with integrity and ethics, I am committed to providing objective and impartial information without any influence or bias from external sources. My sole objective is to present the facts in a transparent manner and to provide recommendations or analyses based on objective criteria and thorough research. I am fully aware of the importance of maintaining an appropriate distance from any potential conflict of interest in order to guarantee the credibility and reliability of the information presented.

Furthermore, research has shown a significant link between income and suicide rates, with lower rates observed among people who do not pay income tax compared to their tax-paying counterparts (Deaton & Stone, 2014). This raises interesting questions about the psychological implications of tax obligations and the potential role of financial burdens in influencing mental wellbeing. Nevertheless, the influence of income on overall happiness shows a diminishing effect, particularly above a baseline threshold (Easterlin, 2005). This means that the pursuit of additional income may not significantly improve the overall sense of happiness or life satisfaction once basic needs are met. Furthermore, the impact of external conditions, such as income, on happiness is relatively small compared to the influence of individual thoughts and behaviours (Lyubomirsky et al., 2005). With these considerations in mind, this article explores the relationship between income and individual happiness in the United States, using data from the General Social Survey (GSS) 2022. To assess this impact, the study adopts an econometric modeling approach, employing, in particular, the exact matching method. This method was chosen to create a balanced control group, facilitating a fair comparison between individuals with different levels of happiness while taking into account potential selection bias.

The rationale for using this methodology is rooted in seminal work on propensity score matching, in particular the studies of Rosenbaum & Rubin (1983). The article highlights the relevance of this approach in answering a crucial question: how do individuals' happiness levels differ according to their income levels? The aim of adopting this method is to ensure a rigorous comparison, to control for selection bias, and to provide information on the nuanced relationship between income and happiness.

This article is structured to provide an in-depth analysis of the relationship between income and happiness. Section 2 presents a comprehensive review of the existing literature, highlighting previous research on the topic. Section 3 then presents the data used for this study, together with stylised facts about income and happiness. Section 4 describes the methodology used for this analysis, including the choice of matching method. Section 5 focuses on the balance check after matching, which ensures the validity of the comparison between the two groups. Section 6 presents and discusses the study's findings in detail. Finally, the article concludes with Section 7, which summarises the main findings of the study, suggests avenues for future research, and offers recommendations for public policy and interventions aimed at improving individual well-being.

2. LITERATURE REVIEW

In the United States, a higher income is associated with a decrease in daily sadness but has no impact on daily happiness (Stevenson & Wolfers, 2008). The initial observation suggests that in the United States, a higher income is linked to a decrease in daily sadness (Stevenson & Wolfers, 2008). This association could be attributed to the alleviation of financial stressors and the increased ability to meet one's basic needs, which contributes to a more stable emotional state. Similarly, Clark, et al. (2017) provided evidence from survey data in the US, Australia, Great Britain, and Indonesia. They found that social relationships and mental and physical health are key determinants of happiness. These adult factors affecting happiness are in turn influenced by the child's developmental pattern; the best predictor of an adult's life satisfaction is their emotional health as a child.

In another line of research, Paul (2022) examined the effects of happiness on income and income inequality. Using data from an Australian HILDA survey (2001–2014), Paul (2022) hypothesised that happiness impacts individuals' ability to generate income, both directly by boosting work efficiency and indirectly by affecting their time allocation for paid work. Its findings demonstrate that happiness has a positive and significant effect on income generation and helps to reduce inequality. However, for another panel, FitzRoy & Nolan (2022) used a large sample of data from the British Household Panel Survey and Understanding Society, covering the period from 1996 to 2017. They applied regression techniques to examine the relative importance of income rank, relative income, and household income as predictors of happiness and life satisfaction. Their results show that all three factors are important, but their importance varies between different sub-groups. This in-depth analysis has led to a better understanding of the factors that influence happiness and life satisfaction. Similarly, D'Ambrosio, et al. (2020) added a further perspective by examining the relationship between money and happiness. They found that permanent income and wealth are better predictors of life satisfaction than current income and wealth. Moreover, they found that the impacts of these factors vary along the distribution of well-being.

Easterlin (2023) studied how people assess their income situation in relation to the state of the economy. He found that when the economy is expanding and incomes are generally rising, people tend to assess their own income by comparing it with that of others, a phenomenon he calls 'social comparison'. However, during a recession, when incomes fall, people tend to evaluate their income by comparing it with their previous maximum income. Easterlin (2023) also discovered an asymmetry in the way happiness responds to changes in income. When income rises, changes in income have, on average, no effect on happiness. However, when income falls below its previous peak, happiness decreases and increases with it. These results suggest that the way in which people evaluate their income, and therefore their happiness, depends on the state of the economy. Their findings suggest that the way people evaluate their income, and therefore their happiness, depends on the state of the economy. However, it's crucial to note that the correlation with daily happiness appears to be non-existent.

Research shows that individuals have lower suicide rates or are "happy" when they do not pay income taxes compared to those who do (Deaton & Stone, 2014). The passage highlights a notable finding that individuals who do not pay income taxes exhibit lower suicide rates or report being "happy" compared to those who pay taxation (Deaton & Stone, 2014). This raises intriguing questions about the psychological and emotional implications of tax obligations. The financial burden associated with income taxes may play a role in individuals' mental well-being.

However, the impact of income on overall happiness is relatively weak, especially when income surpasses a basic minimum (Easterlin, 2005). Despite the positive correlation between higher income and reduced daily sadness, the passage suggests that the impact of income on overall happiness is relatively weak, particularly when income exceeds a basic minimum (Easterlin, 2005). This aligns with research indicating that, beyond a certain threshold, the pursuit of additional income may not significantly contribute to an individual's overall sense of happiness or life satisfaction. In this context, Munir & Nazuk (2019) used a binary logistic regression framework to model the happiness index when converted to a dichotomous level. They collected primary data from various Pakistani regions (rural and urban) through a survey with a sample size of 763. Their results showed a positive and significant relationship for the big five traits (extraversion and neuroticism), confidence in the armed forces, life satisfaction, and age.

External conditions such as income have a relatively weak impact on happiness compared to thoughts and behaviours (Lyubomirsky, et al. 2005). The passage underscores the idea that external conditions, such as income, have a relatively weak impact on happiness compared to thoughts and behaviours (Lyubomirsky, et al. 2005). This aligns with psychological theories that emphasise the importance of individual mindset, coping mechanisms, and behavioural choices in influencing overall well-being. It implies that personal agency and internal factors play a crucial role in determining happiness.

Income comparisons may challenge the law of diminishing marginal utility, which states that a higher income's marginal utility can increase with others' income, leading to a rat race or an arms race (Clark, et al. 2008). This law suggests that as income increases, the additional satisfaction or happiness derived from each additional unit of income decreases. Income comparisons, however, may disrupt this principle by introducing relative considerations, potentially leading to a competitive pursuit of a higher income in comparison to others.

Other studies have attempted to explain individuals' happiness through additional sociodemographic characteristics, such as age (Diener, et al. 1999; Blanchflower & Oswald, 2004) and gender (Louis & Zhao, 2002). For instance, research focusing on the relationship between age and subjective well-being suggests a convex "U" curve, corresponding to higher levels of individual happiness for both the youngest and oldest individuals, with lower subjective well-being observed in the middle age group (between 32 and 50 years) (e.g., Blanchflower & Oswald, 2004; Ferrer-i-Carbonell & Gowdy, 2007). Overall, while a higher income can alleviate sadness and reduce suicide rates, its impact on overall happiness is limited, and other factors such as personal relationships and positive behaviours play a more significant role in determining happiness.

The research exploring the relationship between income and happiness in the United States reveals intricate dynamics with various factors at play. Hutchinson's, et al. (2017) findings add a distinctive perspective, indicating that individuals who are exempt from paying income taxes tend to report higher levels of happiness. This observation raises questions about a potential link between the burden of taxation and individual happiness. In a similar vein, Liao (2021) and Dynan (2007) delve into the impact of social comparison on the income-happiness relationship. Liao specifically highlights the role of income inequality in influencing happiness, emphasising how disparities among individuals can affect their well-being. On the other hand, Dynan proposes that an individual's happiness is shaped by how their socio-economic standing compares to others in society. This underscores the significance of relative income in determining subjective well-being.

Oishi's (2011) contribution adds another layer to this discussion by highlighting the detrimental effects of income inequality on happiness, especially among individuals with lower incomes. Income disparities cause perceived unfairness and a lack of trust, which contributes to lower happiness levels. Together, these studies collectively underscore the multifaceted nature of the income-happiness relationship in the United States, emphasising the roles of income itself, the burden of taxation, and social comparison in shaping individual well-being. For China, Ye, et al. (2023) estimated the causal effect of income on happiness using a unique dataset of Chinese twins. Their results show that individual income has a significant positive effect on happiness, with a doubling of income resulting in a 0.26 scale or 0.37 standard deviation increase in the four-scale happiness measure. Their results underline the importance of accounting for various biases when studying the relationship between socio-economic status and subjective well-being. An inverse line between income and happiness was studied by MA & MA (2021), who examined the influence of income on the subjective happiness of teachers in Chinese private universities. They established a model for measuring teachers' subjective happiness, taking into account the specific characteristics of Chinese private universities. Using the structural equation model to analyse data collected from teachers at private universities in China, they found that income has a significant positive impact on teachers' subjective happiness, in particular through the level of consumption and housing conditions.

Behera, et al. (2024) examined the socio-economic factors that contribute to happiness in 166 developed and developing countries (51 developed, 115 developing). They used robust, two-factor fixed effects and panel-quantile regression for the empirical analysis. Their results show that per capita income, social support, and the freedom to make life choices have a positive impact on happiness, while exposure to air pollution has a negative impact. On the other hand, Kundu, et al. (2024) examined the relationship between democracy, macroeconomic variables, and happiness in 83 countries (low- and high-income countries) from 2010 to 2016. They used a variety of panel data analyses, including the threshold panel model. Their results show that, although GDP per capita has no direct impact on happiness, it does establish the role of other variables in determining happiness. In higher-income countries, democratic quality and inflation have a significant impact on happiness. Furthermore, in low-income countries, inequality and government spending on health per capita have a negative and positive impact, respectively.

3. DATA AND STYLISED FACTS

This section is devoted to presenting the data and stylised facts underlying our analysis. We will describe in detail the data sources used for this study. We will also present a series of stylised facts about income and individual happiness that have been identified from the data. These stylised facts will form the basis of our analysis and help to illuminate the trends that we are attempting to capture.

3.1. Data

Since 1972, the United States has conducted a series of cross-sectional interviews known as the General Social Survey (GSS). The 2022 GSS Cross-section connects the two eras of GSS data collection—the face-to-face era from 1972 to 2018 and the web-based era of 2021. It retains many of the questionnaire changes that occurred during the transition but returns to a mixed-mode data collection strategy that includes face-to-face, web, and telephone. The GSS 2022 was structured to be comparable to the 2018 GSS; in other words, the 2022 research tried to mimic the 2018 GSS. In addition, the GSS 2022 carried over a number of web-specific methodological trials from the GSS 2021. The GSS 2022 marks the beginning of a multi-round shift to a mixed-mode survey, with questions delivered both in-person and online.

There are three distinct occurrences of GSS variables. There isn't much change to the items in the Replicating Core, Household Composition, and Contact/Validation categories, but in 2022, they will have web mode modifications. Certain subject modules, such as ISSP modules, may include items that occur more than once a year, but not every single time. Last but not least, most of the topical modules only release their products once a year. In the GSS 2022, the ISSP Family and Gender Roles, ISSP Health and Health Care, Shared Capitalism, NIOSH Quality of Working Life, National Endowment for the Arts, and High-Risk Behaviours modules are repetitions from prior years. It is vital to note that critical modifications to questions were made to the National Endowment for the Arts (NEA), Shared Capitalism, and NIOSH QWL. The board-initiated module entitled GSS Next contains a blend of traditional and new GSS variables. Table 1 (Column 2) illustrates the definitions and associated descriptive statistics for the important variables in our final sample.

Table 1

Statistics Summary of the Survey Data

Variable	Definitions	Mean	Std. Dev	Min	Max
income	The treatment variable indicates two levels of individuals: 1 for treated and 0 for untreated.	0.6148420	0.4867013	0	1
happiness	The outcome variable indicates if a person is happy (1) or not (0).	0.7734199	0.4186777	0	1
employment_status	Indicates whether the person is working full-time or part-time (1), or whether they are in school or homemaking (0).	0.5996050	0.4900476	0	1
marital_status	Indicates if the person is married (1) or not (0).	0.4844808	0.4998296	0	1
number_of_children	Indicates the number of children in the house.	1.7353273	1.6678576	0	8
age	The individual's age.	46.2911964	20.9220121	0	89
education_level	This represents the person's years of education.	14.0411964	3.0459824	0	20
school_degree	Education level is divided into two groups: less than high school (0), and high school degree or higher (1).	0.8092551	0.3929438	0	1
gender	Indicates if the individual is male (1) or female (0).	0.4590858	0.4983935	0	1
adults_house	Indicates the number of adults in the house.	1.8177201	0.8713859	0	9
health_status	Indicates the health status of the individual: above average (1) or below average (0).	0.7107788	0.4534648	0	1
social_class	Indicates the individual's social class: lower and working class (0), or middle and upper class (1).	0.1529345	0.3599752	0	1
satisfaction_level	Level of satisfaction with the individual's current financial situation: satisfied (1) or not (0).	0.4424379	0.4967456	0	1
unemployment_status	Indicates an individual's employment situation: unemployed (1) or not (0).	0.2200903	0.4143658	0	1

Source: Authors' calculations, R software.

Table 1 paints a detailed picture of the population studied, highlighting two key elements: income and level of happiness. Income distinguishes two categories of individuals: those who are 'treated' (1) and those who are not (0). The level of happiness gives us an insight into the emotional well-being of the population. At the same time, a series of variables offer a more in-depth view of people's lives. Age, gender, marital status, number of children, number of adults in the household, level of education, school qualifications, state of health, social class, level of satisfaction, and employment status are all facets that make up the complex picture of human life.

A closer look reveals that 61 percent of people are 'treated' in terms of income, and 77 percent of people say they are happy. Nearly 60 percent of people work full-time or part-time. Almost half are married, and the average number of children per household is approximately 1.74. The average age is 46, and the vast majority of people have a secondary education or higher. Less than half of the residents are men, and the average number of adults per household is approximately 1.82. A large majority of people are in above-average health, and a small proportion are middle- or upper-class. Less than half of the residents are satisfied with their current financial situation, and a small proportion are unemployed.

3.2. Stylised Facts

3.2.1. *The Happiness Index*

In our study, the outcome variable is the happiness of the household surveyed, obtained from a multiple-choice question: "Overall, how happy are you at the moment?" The three possible answers to this question are: very happy, fairly happy, or not too happy? Happiness is the most widely used indicator in the literature (Ferrer-i-Carbonell and Frijters (2004); Singh, et al. (2023); and Ye, et al. (2023). For our analysis, we construct a binary 'happiness' variable with a value of 1 if the person is very happy and fairly happy, and a value of 0 if the person is not too happy.

Table 2

Distribution of Individual Happiness by "health_status", "social_class", "unemployment_status"

Category	mean_happiness	sd_happiness	variable
0 (not happy)	0.624	0.485	health_status
1 (happy)	0.834	0.372	health_status
0 (not happy)	0.795	0.403	social_class
1 (happy)	0.651	0.477	social_class
0 (not happy)	0.806	0.395	unemployment_status
1 (happy)	0.656	0.475	unemployment_status

Source: Authors' calculations, R software.

Table 2 presents summary statistics for the sample on happiness status in relation to 'health_status','social_class', and 'unemployment_status'. From the data, it is clear that health status and employment status have a significant influence on people's level of happiness. Individuals in good health have an average happiness level of 0.834, which is significantly higher than that of individuals in poorer health, which is 0.624. Similarly, individuals who are not unemployed have an average happiness level of 0.806, compared with 0.656 for those who are unemployed.

On the other hand, social class seems to have an inverse effect on happiness. Individuals from the lower or working class have an average happiness level of 0.795, which is higher than that of those from the middle or upper class, which is 0.651.

3.2.2. *Income Disparity*

Table 3 illustrates the distribution of income as a function of three key variables: ‘health_status’, ‘social_class’ and ‘unemployment_status’. With regard to ‘health_status’, the data indicate a disparity in income between those who are happy and those who are not. Happy individuals have an average income of 0.644, while those who are not happy have an average income of 0.542. This is consistent with the study by Paul (2022), who also found a positive correlation between happiness and income. As far as the ‘social_class’ is concerned, there seems to be a reversal of this trend. Individuals who are not happy have a slightly higher average income (0.629) than those who are happy (0.537). This observation is supported by the work of FitzRoy and Nolan (2022), who also found a similar trend in their study. Finally, with regard to ‘unemployment_status’, the data also show an income disparity. Individuals who are not happy have a slightly higher average income (0.627) than those who are happy (0.573). This might suggest that unemployment can have an impact on happiness levels independently of income.

Table 3

Distribution of Income by “health_status”, “social_class”, “unemployment_status”

category	mean_income	sd_income	variable
0 (not happy)	0.542	0.498	health_status
1 (happy)	0.644	0.479	health_status
0 (not happy)	0.629	0.483	social_class
1 (happy)	0.537	0.499	social_class
0 (not happy)	0.627	0.484	unemployment_status
1 (happy)	0.573	0.495	unemployment_status

Source: Authors’ calculations, R software.

4. METHODOLOGICAL APPROACH

To meet the objective of this study, which is to assess the impact of income on the happiness of individuals in the United States, we chose a methodological approach based on econometric modelling, using the exact matching method (this exact matching technique consists of displaying each treated unit with a control unit having exactly the same values for each covariate). This approach was chosen because it enables us to make a rigorous comparison between individuals with a high level of happiness and those with a low level of happiness, while controlling for selection bias and ensuring a fair comparison between the two groups (those with a high income and those with a low income).

We justify this choice of methodology by drawing on reference works such as those of Rosenbaum & Rubin (1983), who are the founders of the propensity score matching method. This approach is particularly relevant in our context, as it allows us to answer the crucial question: how do individuals' levels of happiness differ from those they would have had if they had no income or a low income?

In terms of data collection and processing, we have chosen to use the US Household Survey (GSS, 2022). This survey will provide us with data on various household characteristics, as well as the factors that influence their level of happiness. To analyse these data, we will use R statistical software, with specific R packages adapted to our analysis needs.

4.1. Model Specification

The challenge is to assess the impact of individual income in the United States, focusing specifically on its effect on their happiness. The variable of interest, as we will call it, represents household incomes. Thus, it would correspond to the result of household I's participation in the treatment group, while it would be the result in the absence of participation. The impact of income on household happiness can be simply expressed as follows:

$$\Delta_i = Y_{1i} - Y_{0i}$$

And the average impact for the entire population is:

$$E(\Delta_i) = E(Y_{1i} - Y_{0i})$$

The complexity lies in the need to simultaneously observe the same household in two distinct states, acting as both a participant and a non-participant for a task that is not performed. In each scenario, we have only de or de, depending on whether or not the household participates in the treatment group (person with above-average income). Impact analysis therefore faces the challenge of estimating missing data. Choosing an impact analysis method means devising a strategy for estimating the missing data. Various approaches are possible with a single measurement over time, such as the experimental method, PSM (propensity score matching), mentioned by Rosenbaum & Rubin (1983), Heckman, et al. (1997), and Caliendo & Hujer (2006).

It's not enough to just compare participants and non-participants; you also need to estimate the unobserved value of variable Y for participants (if they don't have any income) by dividing it by the unobserved value of variable Y for non-participants (people with below-average income). This approach does not allow an accurate estimate of the impact, as will be shown later. To overcome this limitation, we adopt a more rigorous approach. We consider a household i, where D represents the dichotomous variable of people with income above or equal to the average, if household i has income above or equal to the average (treated person) and otherwise. We assume that the variable Y depends on a set of explanatory variables, according to a linear model formulated as follows:

$$Y_{0i} = X_i\beta_{0i} + U_{0i} \textit{ with i=1, ..., n}$$

$$Y_{1i} = X_i\beta_{1i} + U_{1i} \text{ with i=1, …, n}$$

According to the general principle of basic assumptions:

$$E(U_{0i} \mid X_i) = E(U_{1i} \mid X_i) = 0$$

Using these notations, we have:

$$\Delta_i = Y_{1i} - Y_{0i} = X_i(\beta_{1i} - \beta_{0i}) + (U_{1i} + U_{0i})$$

The indicator commonly used to measure impact is the average gain in income for those treated, also known as ATET (Average Treatment Effect on the Treated) in the evaluation literature.

It is calculated as follows:

$$ATET = E(\Delta_i \mid X_i, D_i = 1) = X_i(\beta_{1i} - \beta_{0i}) + E(U_{1i} + U_{0i} \mid X_i, D_i = 1)$$

In the specific case where the variable Y is not influenced by the explanatory variables X, we simply obtain the unconditional mean in X:

$$ATET = E(\Delta_i \mid D_i = 1)$$

If we wish to estimate ATET simply by calculating the difference between participants and non-participants, the estimator is as follows:

$$\begin{aligned} BATET &= E(Y_1 \mid X, D = 1) - E(Y_0 \mid X, D = 0) \\ &= E(Y_1 \mid X, D = 1) - E(Y_0 \mid X, D = 1) + E(Y_0 \mid X, D = 1) \\ &\quad - E(Y_0 \mid X, D = 0) = ATET + BIAIS \\ &\qquad with\ BIAIS = E(Y_0 \mid X, D = 1) - E(Y_0 \mid X, D = 0) \end{aligned}$$

This bias is explained by the fact that households with an income above or equal to the average would have a different level of happiness than households with an income below the average (the control group). In other words, treated and untreated households are not identical. In order to eliminate this bias, the variables $Y_i(0)$ and T_i must be independent.

To confirm the absence of bias in this case, we introduce an additional variable, R, which is a dichotomous variable among potential participants. It takes the value 1 if the household actually participates in the treatment group, and 0 otherwise. Using this new notation, the effect of income on household happiness can be expressed as follows:

$$Y = D(RY_1 + (1 - R)Y_0) + (1 - D)Y_0$$

The impact of income is:

$$\begin{aligned} BATET &= E(Y \mid X, D = 1, R = 1) - E(Y \mid X, D = 1, R = 0) \\ &= E(Y_1 \mid X, D = 1) - E(Y_0 \mid X, D = 1) = ATET \end{aligned}$$

The experimental method offers the possibility of estimating the impact directly because the samples of treated and untreated people share the same observable and unobservable characteristics. However, when the experimental method is not feasible, ‘matching’ techniques, particularly PSM (Propensity Score Matching), offer a credible alternative.

PSM (Propensity Score Matching) is used to create a control group similar to the treatment group (households with an income equal to or greater than the average) from non-experimental data. Using a set of variables Z, which were used to select the participants, the aim is to find a subset of households with similar characteristics in Z. In this way, PSM makes it possible to estimate the impact of income based on participation, just like the experimental method. Among the possible scores, the "propensity score" is often used, representing the probability of participating in the treatment group. For the group to be a valid control group, similar to a random sample of non-participants, two conditions must be met.

These conditions are as follows:

$$(Y_0, Y_1) \perp D \mid Z \qquad \text{And } 0 < \mathrm{P}(Z_i) = E(D_i \mid Z_i) < 1$$

The first hypothesis of PSM assumes that, conditional on Z, the distribution of results for non-participants is the same as that of participants had they not participated (persons with an income equal to or greater than the average).

The second assumption of PSM is that each unit has a positive probability of being selected, which makes it possible to form a control group. However, the difficulty lies in the fact that the pair is orthogonal to D conditional on Z and not on the score function m(Z). Rosenbaum and Rubin (1983) have shown that if it is orthogonal to D conditional on Z, then it is orthogonal to D conditional on m(Z).

The research of Heckman et al. (1997) shows that these assumptions are strict and can be relaxed. To estimate ATET, it suffices that:

$$Y_0 \perp D \mid Z$$

To construct the control group, different algorithms are used to match the observations of the treated and untreated groups. Whatever algorithm is used, the aim is to estimate the ATET (average treatment effect on the treated). Suppose we have a sample of size n for the treated group, where J_i represents the set of matched individuals in the control group for individual i, and $|J_i|$ is the cardinal of J_i. In addition, ω_i denotes the weight associated with each individual from the survey. Under these conditions, we can obtain an unbiased ATET estimator:

$$\hat{\Delta} = \sum_{i=1}^{n} \omega_i \left(Y_{1i} - \frac{1}{|J_i|} \sum_{j=1}^{|J_i|} Y_{0ij} \right)$$

4.2. PSM Implementation

Our study's implementation of Propensity Score Matching (PSM) aims to construct a control group with similar characteristics to the group of people with an income equal to or above the average (participant group) in order to be able to reliably assess the impact of income on the happiness of treated individuals (treatment group). We chose to set up this control group at the household level to ensure the results were robust.

To do this, we used a probit-type regression, taking the status of treated individuals as the dependent variable and including all relevant characteristics that influenced happiness as independent variables. This approach enabled us to predict a propensity score for each household, i.e., the probability of it being a treated person. Then, using an appropriate "matching" algorithm, we matched participating households to non-participating households with similar propensity scores. In this way, we were able to build a balanced control group based on the relevant characteristics, enabling us to better isolate the effect of income on the happiness of people with an income equal to or above the average (treated people).

Checking Post-matching Equilibrium

Before plunging into the analysis of impact results, it is essential to confirm that matching has indeed established a balance between treatment and control groups. Indeed, two main conditions, formulated by Rubin (1973) and Rosenbaum & Rubin (1983), are essential to guarantee equilibrium between treatment and control groups. The crucial element in our analysis is conditional equilibrium, which states that treatment assignment is independent of the potential outcome once covariates are taken into account. In other words, the probability of being subjected to a treatment should not be associated with potential outcomes after adjusting for covariates. This ensures that our analysis is robust and minimises selection bias.

Table 4 shows a post-matching comparison of characteristics between treatment and control groups. It is remarkable that for all variables, the treatment and control groups' means are identical, indicating perfect equilibrium after matching. Furthermore, the standardised mean difference is zero for all variables, reinforcing the idea of perfect equilibrium.

In terms of sample size, we initially have 1365 individuals in the control group and 2179 in the treatment group. After matching, we have an almost perfectly matched sample with 30 individuals in the control group and 29 in the treatment group. The number of unmatched individuals is 1335 in the control group and 2150 in the treatment group.

Table 4

Comparison of Characteristics After Matching between Treatment and Control Groups

	Summary of Balance for Matched Data		
	Means Treated	Means Control	Std. Mean Diff.
employment_status	0.7241	0.7241	0
marital_status	0.4483	0.4483	0
number_of_children	1.2069	1.2069	0
age	34.3793	34.3793	0
education_level	14.6207	14.6207	0
school_degree	0.9655	0.9655	0
gender	0.4828	0.4828	0
adults_house	1.6207	1.6207	0
health_status	0.9310	0.9310	0
social_class	0.0000	0.0000	0
satisfaction_level	0.4483	0.4483	0
unemployment_status	0.0345	0.0345	0
	Sample Sizes		
	Control	**Treated**	
All	1365	2179	
Matched (ESS)	26.7	29	
Matched	30	29	
Unmatched	1335	2150	

Source: Authors' calculations, R software.

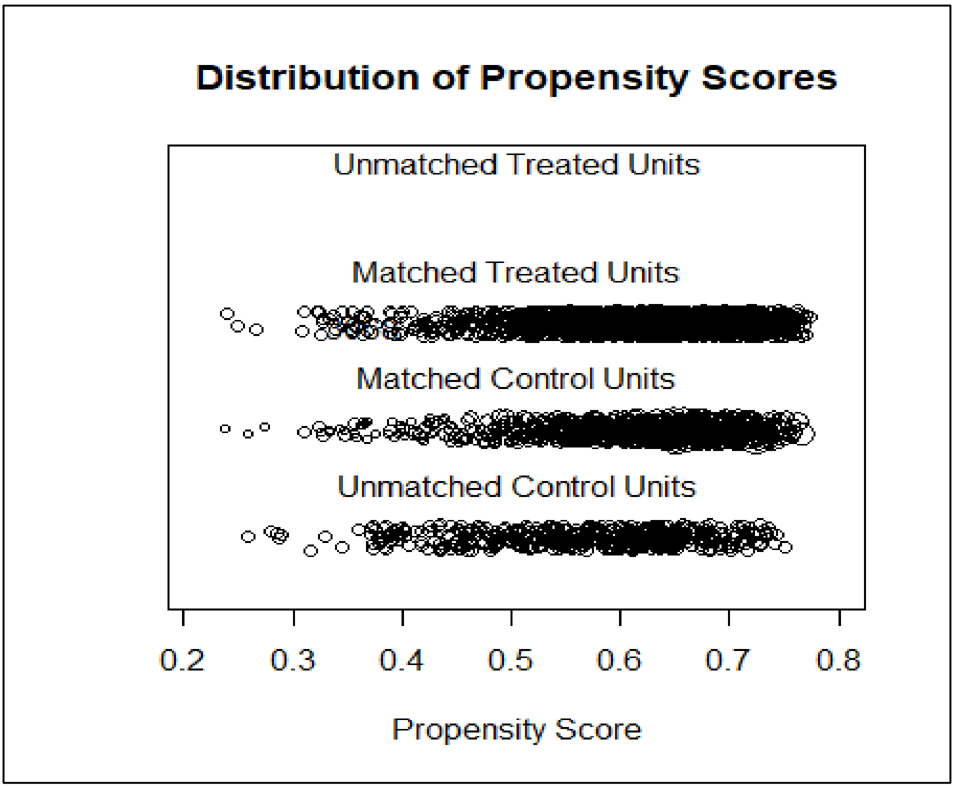
Figure 1 illustrates four histograms showing the distribution of propensity scores for the treatment and control groups, before and after matching. The "Raw Treated" and "Raw Control" histograms show that the treatment and control groups' propensity score distributions were not the same before they were matched. This means that the two groups cannot be compared based on visible characteristics. However, the "Matched Treated" and "Matched Control" histograms show that after matching, the propensity score distributions for the treatment and control groups became very similar. This shows that matching was successful in making the two groups comparable. These observations suggest that the common support hypothesis, which states that there must be treated and untreated individuals for each propensity score, is satisfied after matching. This strengthens the validity of the subsequent analysis of the impact results on the relationship between income and happiness.

Fig. 1. The Distribution of Propensity Scores for Treatment and Control Groups after Matching

Source: Authors' calculations, R software.

Figure 2 illustrates the distribution of propensity scores for treated and untreated units, before and after matching. The dots on the graph represent the individual propensity scores for each unit. We observe that matched units (treated and control) have more concentrated distributions around the mean propensity scores, while unmatched units (treated and control) are more widely dispersed over the range of propensity scores. This figure demonstrates how well matching worked by aligning the distribution of propensity scores for the treatment and control groups. This suggests that matching worked to make the two groups similar in terms of observable characteristics, which strengthened the validity of the next impact outcome analysis.

Fig. 2. The Distribution of Propensity Scores for Treatment and Control Groups after Matching



Source: Authors' calculations, R software.

5. RESULTS AND DISCUSSIONS

In this section, we analyse the impact of income on household happiness in the United States and assess the quality of the methodology used in this study. First, we examine the impact of income on household happiness by presenting and discussing our analysis's results. Second, we will conduct checks to ensure the matching method's reliability and robustness. These two aspects will enable us to provide a complete and rigorous analysis of the relationship between income and individual happiness.

5.1. The Impact of Income on Happiness

Table 4 illustrates the significant impact of income on happiness. According to our regression results, there is a significant positive relationship between income and happiness. More specifically, each increase of one unit of income (i.e., from an untreated to a treated state) leads to an average increase in happiness of 0.04389, all other things being equal. This estimate is statistically significant at the 1 percent level (p-value = 0.00779 < 0.01), suggesting a substantial positive effect of income on happiness levels. This corroborates the findings of Hutchinson (2017), who found that those who are exempt from income tax tend to report higher levels of happiness.

Our results suggest that improving income could be an effective strategy for increasing individuals' happiness levels. This seems to be in line with the work of Liao (2021) and Dynan (2007), who have highlighted the importance of social comparison and income inequality in determining happiness. However, it is important to note that although our study shows a positive effect of income on happiness, the impact of income inequality and social comparison should not be neglected.

Table 5

Impact of Income on Individual Happiness

Variable	Estimate	Std. Error	t value	P > |z|
(Intercept)	0.74776	0.01388	53.860	< 2e-16 ***
income (1 vs 0)	0.04389	0.01648	2.663	0.00779 **

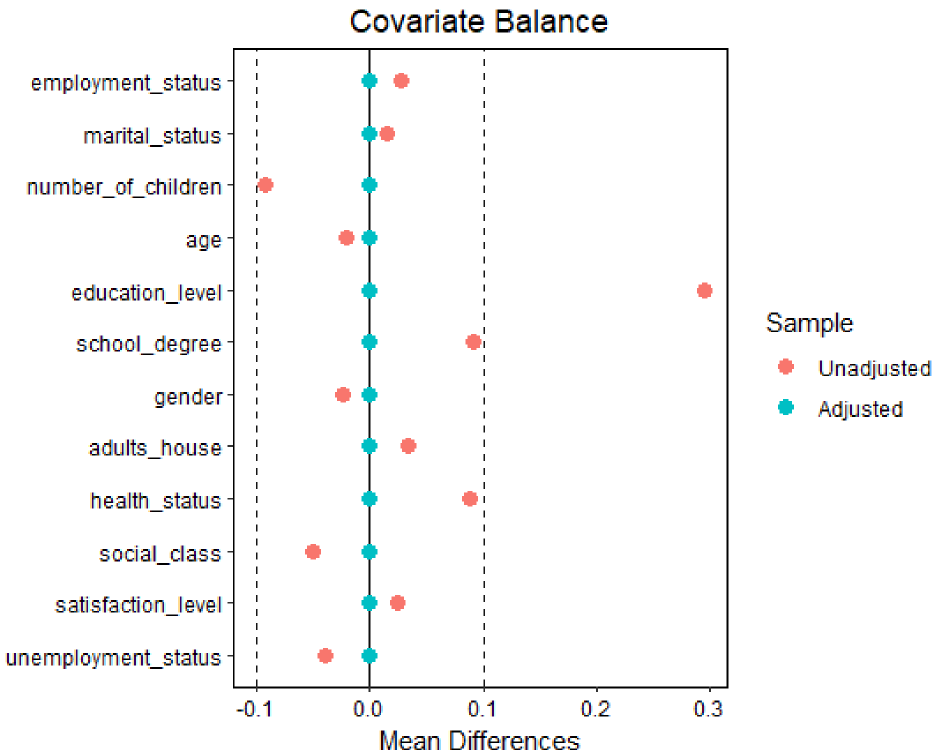
Source: Authors' calculations, R software.
Notes: *** P < 0.001, **P < 0.01.

5.2. Match Quality Checks

The matching quality used in our work is shown graphically in figure 3, which illustrates the balance of covariates, which are potentially confounding variables, before and after mating. The y-axis shows the various covariates. These covariates have been carefully selected for their potential relevance to our treatment variable, "income," and our outcome variable, "happiness." The x-axis represents the mean differences between the treatment and control groups for each covariate. Before matching, represented by the red dots, we observe a significant dispersion of mean differences, indicating a notable imbalance between treatment and control groups. This suggests that, in the absence of matching, any comparison between treatment and control groups could be biased by these differences.

However, after the matching, represented by the blue dots, the mean differences are significantly close to zero. This indicates that the matching has succeeded in creating treatment and control groups that are comparable in terms of covariables. In other words, for each covariable, the treatment and control groups have similar mean values, suggesting that they are well balanced (Ho, et al. 2007). In conclusion, the matching succeeded in minimising average differences between treatment and control groups for all covariables. This improves the study's validity by controlling potential confusion factors. Therefore, any difference observed in the result variable, "happiness," between the treatment and control groups can be attributed with greater confidence to the treatment variable, "income," rather than to differences in the covariables.

Fig. 3. The Balance of Covariables



Source: authors' calculations, R software.

6. CONCLUSION AND POLICY RECOMMENDATIONS

The article concludes that income has a significant impact on individual happiness in the United States, with higher income levels being associated with elevated levels of happiness. The study employs PSM analysis and the general principle of basic assumptions to comprehend the causal relationship between income and happiness. These findings are in line with the work of Hutchinson (2017), who found that those who are exempt from income tax tend to report higher levels of happiness. However, our findings add a new dimension to this discussion by showing that increasing income can actually increase the level of happiness of individuals, regardless of their tax status.

Furthermore, our results seem to be in line with the work of Liao (2021) and Dynan (2007), which highlighted the importance of social comparison and income inequality in determining happiness. However, it is important to note that, while our study highlights the positive effect of income on happiness, it does not overlook the importance of other factors that can influence this relationship. In particular, Liao (2021) and Dynan (2007) highlight the importance of social comparison and income inequality in determining happiness. Furthermore, Oishi's study (2011) highlights the adverse effects of income inequality on happiness among low-income people.

It is also important to note the limitations of this study. Although we found a significant relationship between income and happiness, our study focuses on the United

States, and the results may not be generalisable to other countries or regions. Furthermore, our study does not address the long-term effects of income on happiness and does not take into account other factors that may influence individual well-being, such as inflation and the level of stability of economies that can affect the income of individuals. Furthermore, our study does not deal with the temporal dynamics of happiness. Happiness is an emotional state that can fluctuate over time in response to various life events. Therefore, a longitudinal analysis that follows the same individuals over time could provide more accurate information on the relationship between income and happiness.

Based on these findings, it is recommended that policymakers take into account not only income but also other factors such as social comparison and income inequality when designing policies to improve people's happiness. Indeed, policies aimed at reducing income inequality, improving social support, and promoting the freedom to make life choices could help increase overall happiness. Furthermore, given the impact of income tax exemptions on happiness, tax policies could also be considered as a means of improving well-being. These recommendations could help steer public policy towards 'creating well-being' rather than 'creating wealth'.

REFERENCES

Behera, D. K., Padmaja, M., & Dash, A. K. (2024). Socioeconomic determinants of happiness: Empirical evidence from developed and developing countries. *Journal of Behavioural and Experimental Economics, 109*, 102187.

Blanchflower, D. G. & Oswald, A. J. (2004). Well-being over time in Britain and the USA. *Journal of Public Economics*, *88*(7-8), 1359–1386.

Caliendo, M. & Hujer, R. (2006). The microeconometric estimation of treatment effects—an overview. *Allgemeines Statistisches Archiv, 90*, 199–215.

Clark, A. E., Flèche, S., Layard, R., Powdthavee, N., & Ward, G. (2017). The key determinants of happiness and misery.

Clark, A. E., Frijters, P., & Shields, M. A. (2008). Relative income, happiness, and utility: An explanation for the Easterlin paradox and other puzzles. *Journal of Economic Literature*, *46*(1), 95–144.

D'Ambrosio, C., Jäntti, M., & Lepinteur, A. (2020). Money and happiness: Income, wealth and subjective well-being. *Social Indicators Research, 148*(1), 47–66.

Deaton, A. & Stone, A. A. (2014). Evaluative and hedonic wellbeing among those with and without children at home. *Proceedings of the National Academy of Sciences*, *111*(4), 1328–1333.

Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin*, *125*(2), 276.

Dynan, K. E. & Ravina, E. (2007). Increasing income inequality, external habits, and self-reported happiness. *American Economic Review*, *97*(2), 226–231.

Easterlin, R. A. (2005). Building a better theory of well-being. *Economics and happiness: Framing the Analysis*, 29–64.

Easterlin, R. A. (2023). Why does happiness respond differently to an increase vs. decrease in income? *Journal of Economic Behaviour & Organisation, 209*, 200–204.

Ferrer-i-Carbonell, A. & Frijters, P. (2004). How important is methodology for the estimates of the determinants of happiness? *The Economic Journal*, *114*(497), 641–659.

Ferrer-i-Carbonell, A. & Gowdy, J. M. (2007). Environmental degradation and happiness. *Ecological Economics*, *60*(3), 509–516.

FitzRoy, F. R. & Nolan, M. A. (2022). Income status and life satisfaction. *Journal of Happiness Studies*, *23*(1), 233–256.

Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies, 64*(4), 605–654.

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis*, *15*(3), 199–236.

Hutchinson, T., Ahmed, I., & Buryi, P. (2017). Impact of income tax on happiness: Evidence from the United States. *Applied Economics Letters*, *24*(18), 1277–1279.

Kundu, S., Kundu, R., & Chettri, K. B. (2024). Asymmetric effects of democracy and macroeconomic factors on happiness under high and low per capita incomes: A threshold panel analysis. *Ecological Economics, 216*, 108030.

Liao, T. F. (2021). Income inequality, social comparison, and happiness in the United States. *Socius*, *7*, 2378023120985648.

Louis, V. V., & Zhao, S. (2002). Effects of family structure, family SES, and adulthood experiences on life satisfaction. *Journal of Family Issues*, *23*(8), 986–1005.

Lyubomirsky, S., King, L., & Diener, E. (2005). The benefits of frequent positive affect: Does happiness lead to success? *Psychological Bulletin*, *131*(6), 803.

Ma, G., & Ma, C. (2021). Modelling the impacts of income on the subjective happiness: An empirical study. *Discrete Dynamics in Nature and Society*, 2021, 1–7.

Munir, R. & Nazuk, A. (2019). A micro level study explaining happiness level in Pakistan. *NUST Journal of Social Sciences and Humanities, 5*(1), 63–86.

Oishi, S., Kesebir, S., & Diener, E. (2011). Income inequality and happiness. *Psychological Science*, *22*(9), 1095–1100.

Paul, S. (2022). Effects of happiness on income and income inequality. *Journal of Happiness Studies*, *23*(3), 1021–1041.

Rosenbaum, P. R. & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55.

Rubin, D. B. (1973). The use of matched sampling and regression adjustment to remove bias in observational studies. *Biometrics*, 185–203.

Singh, S., Kshtriya, S., & Valk, R. (2023). Health, hope, and harmony: a systematic review of the determinants of happiness across cultures and countries. *International Journal of Environmental Research and Public Health*, *20*(4), 3306.

Stevenson, B. & Wolfers, J. (2008). *Economic growth and subjective well-being: Reassessing the Easterlin Paradox* (No. w14282). National Bureau of Economic Research.

Ye, M., Zhang, J., & Li, H. (2023). Twins, income, and happiness: Evidence from China. *Proceedings of the National Academy of Sciences*, *120*(25), e2221884120.